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A Prediction Framework for Turning Period Structures in COVID-19 Epidemic and Its Application to Practical Emergency Risk Management

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Abstract The aim of this paper is first to establish a general prediction framework for turning (period) term structures in COVID-19 epidemic related to the implementation of emergency risk management in the practice, which allows us to conduct the reliable estimation for the peak period based on the new concept of "**Turning Period**" (instead of the traditional one with the focus on "Turning Point") for infectious disease spreading such as the COVID-19 epidemic appeared early in year 2020. By a fact that emergency risk management is necessarily to implement emergency plans quickly, the identification of the Turning Period is a key element to emergency planning as it needs to provide a time line for effective actions and solutions to combat a pandemic by reducing as much unexpected risk as soon as possible. As applications, the paper also discusses how this "Turning Term (Period) Structure" is used to predict the peak phase for COVID-19 epidemic in Wuhan from January/2020 to early March/2020. Our study shows that the predication framework established in this paper is capable to provide the trajectory of COVID-19 cases dynamics for a few weeks starting from Feb.10/2020 to early March/2020, from which we successfully predicted that the turning period of COVID-19 epidemic in Wuhan would arrive within one week after Feb.14/2020, as verified by the true observation in the practice. The method established in this paper for the prediction of "**Turning Term (Period)**

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Structures” by applying COVID-19 epidemic in China happened early 2020 seems timely and accurate, providing adequate time for the government, hospitals, essential industry sectors and services to meet peak demands and to prepare aftermath planning, and associated criteria for the Turning Term Structure of COVID-19 epidemic is expected to be a useful and powerful tool to implement the so-called “dynamic zero-COVID-19 policy” ongoing basis in the practice.

Keywords prediction framework; turning period structure; turing phase; COVID-19 epidemic; emergency risk management; emergency plan; Delta and Gamma; iSEIR; spatio-temporal model; supersaturation phenomenon; multiplex network; dynamic zero-COVID-19 policy

1 The Introduction of the Background and Related Literature

Infectious disease epidemics always present challenges to human society, threatening the safety of human life and causing social upheaval and economic losses. In recent years, novel virus infection outbreaks have been increasing globally, from the 2003 SARS-CoV, the H1N1 influenza A in 2009, the MERS-CoV in 2012, the Ebola in 2015, the Chai in 2016, the H5N7 avian influenza in 2017, to the current corona-virus infection (COVID-19). These outbreaks have brought great loss to human life, disrupted population movement, and adversely impacted global development.

In this study, we first extend our iSEIR model given by Yuan, et al.[1] to describe the progression of COVID-19 daily cases in Wuhan, then propose a new concept called “**Turning period**”, or “**Turning Phase**”, which would play a very important role in assisting better plans for the time frame from the perspective of emergence risk plans, in particular for associated looking forward planning such as the battle with the current going on due to pandemics of COVID-19 worldwide since early year of 2020.

By assessing the performance of our iSEIR model to predict the timeline of the spread of COVID-19 in Wuhan since late December 2019 under the help of our new concept of “Turning Period Structure (Turning Term)” to predict the control of the epidemic outbreak measured by a reduction in the number of people infected, it shows that our iSEIR model (see Yuan, et al.[1] for more in details), an extension of the SEIR model, describes the spread and behavior of infectious diseases for individuals under the framework of a probability perspective works well to accurately predicted that “the COVID-19 situation in China would peak around middle to late February as early as Feb.7, 2020”. By combining with the case study in this paper, we like to emphasize that the identification of the “**Turning (Time) Period**” is a key element to have a successful implementation in supporting the emergency plan as it must provide a timeline for effective actions and solutions to combat a pandemic by reducing as much unexpected risk as soon as possible. Our study also indicates that the implementation of the emergency program in the practice associated with the “Isolation Control Program (or, say, “Quarantine Program” in Wuhan (see Begley[2]))” since Jan.23, 2020 by China in Wuhan, and other cities and places in domestic level may be a good experiences by other countries and regions to take a lesson.

During almost last century, in the study and modelling mechanics of infectious diseases, the traditional model called “SEIR” denoted for infectious disease dynamics susceptible-exposed-infectious-resistant and its various (deterministic) versions have been introduced and been very popular in analyzing and predicting the development of an epidemic (see Liu, et al.[3], Murray[4],

Wu, et al.[5,6], Prem, et al.[7], Li, et al.[8], Lin, et al.[9], Kuniya[10], Roosa, et al.[11] and references wherein). The SEIR models the flows of people between four states (the susceptible state variable "S", the exposed variable "E", the infected variable "I", and the resistant variable "R"). Each of those variables represents the number of people in those groups. Take COVID-19 as one example, assume that the average number of exposed cases that are generated by one infected person of COVID-19, this number could be regarded as the so-called "basic reproduction number" (which is indeed the expected number of cases directly generated by one case in a population where all individuals are susceptible to infection), the study on the basic reproduction number, related features for the globally stable endemic, disease-free equilibria, and thresholds is always the main stream for people from the academic research community to the practice in the subject of epidemic disease spread behavior and related social issues.

On the other hand, a great deal and effort have been done for the study on the process and evolution of the limits of the Basic Reproduction Number and similar thresholds in predicting global dynamics of epidemics. In particular, since the occurrence of COVID-19 later December, 2019 in Wuhan, the study on the impact such as how serious the outbreak of infectious disease to the society, and to prediction how many people would be infected to become infectious, and so on, have been attracted by a large number of scholars with reports, see Cao, et al.[12,13], Cowling and Leung[14], Hermanowicz[15], Li, et al.[16], Guan, et al.[17] and reference wherein.

Moreover, modelling the situation of COVID-19 and effects of different containment strategies in China with dynamic differential equations and parameters estimation have also been paid a lot attention by a number of scholars, e.g., see Gu, et al.[18], Hu, et al.[19], Zhao, et al.[20], Yan, et al.[21], Wang, et al.[22], Tang, et al.[23], Huang, et al.[24], Cui and Hu[25], Huang, et al.[26], Ross[27], Jia, et al.[28] and related references wherein. We also like to mention that in their papers, i.e., Jia, et al.[28] discussed the population flow based on spatio-temporal distribution due to the COVID-19 in China as early in 2020, and Yuan, et al.[29] also provided some initial study for the predication of peak period by using the new concept of Turning Phase for the COVID-19 epidemic in China with the data from January/2020 to February/2020.

In particular, Professor Murray[4] leads his IHME COVID-19 health service utilization forecasting team to work on the estimates of predicted health service utilization and deaths due to COVID-19 by day for the next 4 months for each state in the US. Their objective is to determine the extent and timing of deaths and excess demand for hospital services due to COVID-19 in the US (also, see the study of Kuniya[10] on Japan, Murray[4] on USA, Wu, et al.[5,6], Prem, et al.[7] on China).

It seems that almost all of them still follow the way to pay the attention mainly on modelling or forecasting the behavior of spread for epidemic disease directly related to those infected who also become infectious, i.e., the variable "I" of SEIR model, but not much useful study pays the attention to establish a general framework for the prediction of the critical turning period for the spread of pandemic diseases (e.g., the outbreak of COVID-19 epidemic and related issues in the practice) in general.

The object of this paper is to fill in this gap as we do believe that it is so important to study the general dynamics for the outbreak of COVID-19 in each country or regions, which faces a simple expectation that how to find in which time period the battle with COVID-19

would be under controlled? By a fact that for any infectious disease, it should be accepted that in general it is impossible to find or identify the exact turning time point (the so-called the "critical point") for a pandemic associated with various dynamics and associated uncertainty! However, by using a new idea to think of the a "time period" (which is a period of time interval), instead of an exact time point to identify the possible main change for the dynamic behavior of epidemic by using the indicators such as the "number of infectious people" (denoted by I) has been significantly reduced, plus the "population of the exposed" (denoted by E) is also under the control to reach certain limited level below, then in this way, it is possible for us to identify and define different phases and stages for the mechanics of infectious disease spreading incorporating under the supporting by some useful tools such as the iSEIR for which we introduced in [1] with quantitative analysis.

The goal of this paper is to establish a general framework of the turning term (period) structure for COVID-19 epidemic related to the implementation of emergency risk management in the practice, which allows us to conduct the reliable predication for "turning period" (not the traditional way mainly focus on "turning point" anymore) for the case study such as the COVID-19 epidemic in China early in year 2020. By a fact that emergency risk management is always associated with the implementation of an emergency plan, the identification of the Turning Time Period is key to emergency planning as it provides a time line for effective actions and solutions to combat a pandemic by reducing as much unexpected risk as soon as possible, we also discuss how this "turning Term (period) structure" is used to predict the peak phase for COVID-19 epidemic in Wuhan from Jan./2020 to early March/2020. Indeed, based on the observed available daily data of COVID-19 in Wuhan from Jan.23/2020 to Feb.10/2020 as the input, the framework established in this paper is capable to provide the trajectory of COVID-19 cases dynamics for a few weeks starting from Feb.10/2020 to early March/2020, from which we successfully predicted that the turning period of COVID-19 epidemic in Wuhan would arrive within one week after Feb.14/2020, as verified by the true observation in the practice.

The method established in this paper for the prediction of the turning term structure for COVID-19 epidemic in China early 2020 seems timely and accurate, providing adequate time for the government, hospitals, essential industry sectors and services to meet peak demands and to prepare aftermath planning, and associated criteria for the Turning Term Structure of COVID-19 epidemic is expected to be a useful tool for us to implement the so-called "dynamic zero-COVID-19 policy" ongoing basis in the practice.

This paper consists of five Sections as follows. Section 1 is for the background of current study. Section 2 is mainly to explain the challenges faced by the emergency mechanism of epidemic prevention and control of infectious diseases global today, what the our iSEIR dynamic model with multiplex networks looks like as a tool to help us to establish the framework for the prediction of turning period (for such as COVID-19 epidemic required) for emergency risk management in the practice which is discussed in Section 3. In Section 3, we introduce the key and new concept called "Turning Period (Phase)" based on our iSEIR model for the emergency Implementation response in an epidemic infectious disease happened in Wuhan early in 2020. In Section 4, we conducted the case study to show our prediction for the "Peak Period" of COVID-19 in Wuhan, China as early from January/2020 to February/2020. The Section 5 is the

summary for what we learned from the implementation of the risk management in dealing with COVID-19 in Wuhan, China early in 2020, and how the framework established in this paper for the prediction of turning term (phase) structure for the COVID-19 epidemic infectious disease seems timely and accurate, providing adequate time for the government, hospitals, essential industry sectors and services to meet peak demands and to prepare aftermath planning, and associated criteria for the turning term structure (for such as COVID-19 epidemic and related ones) is expected to be a useful tool for us to implement the so-called "dynamic zero-COVID-19 policy" with supporting ongoing basis in the practice.

2 The Challenges by the Emergency Mechanism of Epidemic Prevention in the Practice

The key idea of the "SEIR Epidemic Model" can be traced back to Dr. Ronald Ross who received the Nobel Prize for Physiology or Medicine in 1902 for his work on malaria which laid the foundation for combatting the epidemic disease (see [1]). In 1927, Kermack and McKendrick formulated a simple deterministic model called SIR to describe the dynamic mechanism for directly transmitted viral or bacterial agent in a closed population (see [30]). Since then, scholars have contributed and advanced this field; A significant milestone in the study of Epidemics was the publication of "The Mathematical Theory of Infectious Diseases" in 1957 by Bailey (see [31]). Of these, the famous SEIR model, a core subject in Epidemic discipline (see [5]), like mentioned above, is the basis for describing the mechanism for the spread of infectious diseases, and has been used in a number of research projects and related applications. In the SEIR model, as mentioned above, the "S" state refers to the susceptible group (or ignorants) who are susceptible to disease but have not been infected yet; the "E" state refers to the exposed group who are infected but are not infectious yet (or lurkers); the "I" state refers to those infected who also become infectious; and the "R" state refers to those who have recovered from the infection (through treatment or natural recovery) who may or may no longer be infectious, or those who have passed away.

2.1 The Key Issues of Emergency Mechanism for Epidemic Prevention in the Practice

Infectious diseases have always been a major challenge to human society, threatening the safety of human life and causing social upheaval and economic losses. Every scenario of an epidemic outbreak due to a novel infectious disease carries a similar set of challenges: The unknown nature of the new pathogen/strain, a lack of immediate effective treatment and vaccine, and an ill-prepared public health infrastructure to accommodate the surge in potential patients and need for testing. Public health policies that could alleviate and help prevent the impact and scale of an outbreak require significant and massive governmental and societal implementation of emergency planning and intervention strategies. At present, we want to focus the objective of this paper towards "**three key issues**" below in approaching these outbreaks:

1. **How do we establish a spatiotemporal model for the infectious diseases' outbreak:** In order describe the mechanics of the spread of infectious diseases?

2. **How do we conduct numerical simulation and risk prediction indicators:** In

order to conduct numerical simulation based on the real scenes, which can be used to provide an outlook and planning schedule associated with a key period known as the "**Turning Phase**" during the spread of infectious diseases?

3. **How do we carry out effective predictive analysis on the epidemic situation of infectious diseases on an ongoing basis:** In order to cooperate with dynamic management, support public health emergency plans/services, and support community responses by establishing a coherent bigdata method for data fusion from different sources with different structure.

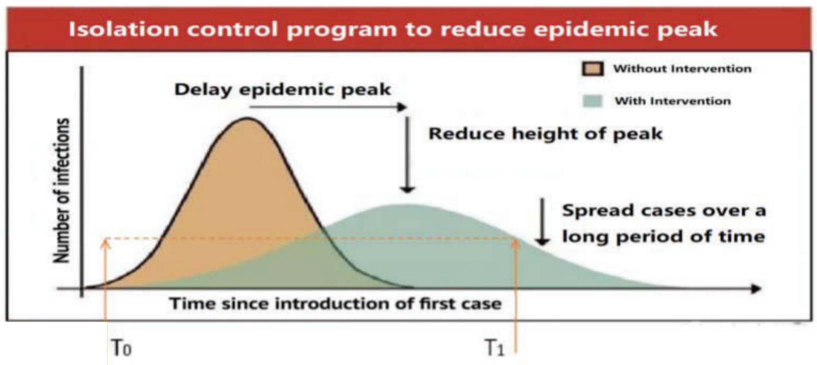

Figure 1 The outlook isolation control program to reduce epidemic peak

In combatting these outbreaks, the immediate implementation of an emergency response mechanism delays an epidemic's peak which affords us more time to control the epidemic by reducing the number of infections in a concentrated period of time. Thus, a successful emergency plan lengthens the "Turning Phase" (or say, "Turning time Period" (see [32–34]), as shown by Figure 1 for the time interval "**Between $\mathbf{T}_0$ and $\mathbf{T}_1$**". Effective ways of flattening the curve include intervention actions such distancing or isolation programs (e.g., see quarantine program and related issues discussed in [2], [34–36] and related references).

Thus, a major challenge faced by our current responses to epidemic prevention and infectious disease control is finding a way to predict the critical time period "**Turning Period (Phase)**" or, saying "**Turning Term**" when implementing an emergency plan. Knowing this timeline is critical to combat the outbreak of an epidemic or infectious disease.

In this section, we discuss the framework for the "Turning Phase" under the framework of the "**iSEIR**" model introduced by Yuan, et al.[1] which was used to predict the "Turning Phase" for the COVID-19 epidemic from January 2020 to early March 2020 in China using only data from Feb.10, 2020. Here we first give a brief introduction for the iSEIR model, which stands for the name "**individual Susceptible-Exposed-Infective-Removed**".

2.2 The Framework of the iSEIR Dynamic Model with Multiplex Networks

For the convenience of our discussion, we give an introduction on the general framework of our iSEIR model which was introduced in [1] for more in details and numerical simulations lined to the applications.

In one word, our iSEIR model operates under a probability perspective for each individual with the name "individual Susceptible-Exposed-Infective-Removed (iSEIR)", which is an extension of the classic SEIR one. The iSEIR model allows us to conduct simulations from the individual levels located on the nodes of different community networks by incorporating its uncertainty with the probability to conduct random simulation in the corresponding multiplex network.

2.2.1 The Classical SEIR Model

For the SEIR model, we also use $S(t)$, $E(t)$, $I(t)$ and $R(t)$ to represent the proportion of the population being in state S, E, I and R at time t, respectively. In the present case, the system of ODEs describing the dynamics of an SEIR epidemic model thus has the following form:

$$\begin{cases} \dfrac{\mathrm{d}S}{\mathrm{d}t} = -\mu(k)SE, \\ \dfrac{\mathrm{d}E}{\mathrm{d}t} = \mu(k)SE - \beta EI, \\ \dfrac{\mathrm{d}I}{\mathrm{d}t} = \beta EI - \lambda I, \\ \dfrac{\mathrm{d}R}{\mathrm{d}t} = \lambda I, \end{cases} \tag{1}$$

where μ is the rate at which an exposed individual becomes infective, λ is the recovery rate, and with normalization condition (each variable is in percentage change)

$$S(t) + E(t) + I(t) + R(t) = 1 \tag{2}$$

for $t > 0$ (e.g., the case that population considered keeps in a certain amount).

The above deterministic SEIR model and its generalizations have received a lot of attention from various researchers. Indeed, the SEIR model represents more accurately the spread of an epidemic than the corresponding SIR model that does not take into account the latent period. The SEIR model has a slower growth rate, since after the pathogen invasion the susceptible individuals need to pass through the exposed class before they can contribute to the transmission process, as shown by Figure 2A below:

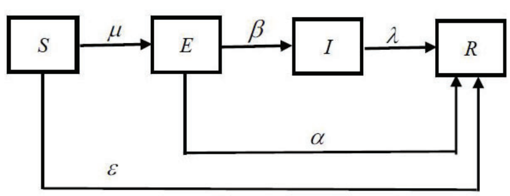

Figure 2A iSEIR model illustration

2.2.2 The Framework of iSEIR Dynamic Systems with Multiplex Networks

Based on the former discussion, the iSEIR (see Figure 2B below on the iSEIR model Illustration below) is an extension of SEIR model, but presented in different expression, which is a

component form as follows in Equation (3).

$$\begin{cases} \dfrac{\mathrm{d}S}{\mathrm{d}t} = A - S(t)E(t)\sum_i \mu_i \sum_j p_{ij} - S(t)\sum_i \varepsilon_i, \\ \dfrac{\mathrm{d}E}{\mathrm{d}t} = S(t)E(t)\sum_i \mu_i \sum_j p_{ij} - E(t)I(t)\sum_j \beta_j \sum_k q_{jk} - E(t)\sum_j \alpha_j, \\ \dfrac{\mathrm{d}I}{\mathrm{d}t} = E(t)I(t)\sum_j \beta_j \sum_k q_{jk} - I(t)\sum_k \lambda_k, \\ \dfrac{\mathrm{d}R}{\mathrm{d}t} = S(t)\sum_i \varepsilon_i + E(t)\sum_j \alpha_j + I(t)\sum_k \lambda_k, \end{cases} \tag{3}$$

where, parameters in the systems are illustrated as follows: A is the growth rate of new arrivals; μ denotes the transfer probability from $S(t)$ to $E(t)$; p_{ij} denotes the connection probability of the i-th sample in $S(t)$ to the j-th sample in $E(t)$; it equal to 1 if connected or 0 if not; ε_i denotes the transfer probability from $S(t)$ to $R(t)$, which is the removed probability; β_j denotes the transfer probability from $E(t)$ to $I(t)$; q_{jk} denotes the connection probability of the j-th sample in $E(t)$ to the k-th sample in $I(t)$; it equal to 1 if connected or 0 otherwise; α_j denotes the transfer probability from $E(t)$ to $R(t)$; and λ_k denotes the transfer probability from $I(t)$ to $R(t)$. The proposed iSEIR model is shown as in Figure 2B (on iSEIR model Illustration):

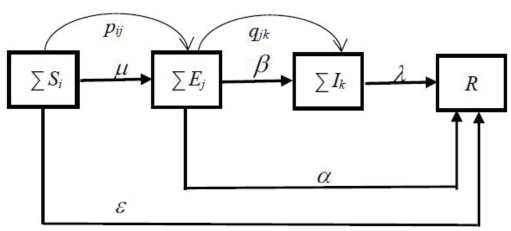

Figure 2B iSEIR model illustration

In order to make the system (3) short and analyze easily, we use the following notations:

$$\begin{cases} \mu = \sum_i \mu_i; \quad \varepsilon = \sum_i \varepsilon_i; \quad \alpha = \sum_j \alpha_j; \quad \beta = \sum_j \beta_j; \quad \lambda = \sum_k \lambda_k; \\ p = \sum_i \sum_j p_{ij}; \quad q = \sum_j \sum_k q_{jk}. \end{cases} \tag{4}$$

As our iSEIR model is based on the framework of multiplex networks for the community of the population, we first give a brief description on the notations used by the reference [1].

By supposing the population S related to COVID-19 epidemic consists of N individuals $S_j, j = 1, 2, \cdots, N$; namely $S := \{S_j, j = 1, 2, \cdots, N\}$; and also suppose these N individuals are distributed over the number being M of continuous domains $U_i, i = 1, 2, \cdots, M$, where a domain may refer to a residential district or a network. Then we can conduct the simulation based on framework of probability respective for each individual based on iSEIR in a population multiplex network by following five steps.

Step 1 We first allow the transition from state S to state R directly with probability ε per unit time (the same below) by following equation:

$$\begin{cases} \dfrac{\mathrm{d}S}{\mathrm{d}t} = A - \mu SE - \varepsilon S, \\ \dfrac{\mathrm{d}E}{\mathrm{d}t} = \mu SE - \beta EI - \alpha E, \\ \dfrac{\mathrm{d}I}{\mathrm{d}t} = \beta EI - \lambda I, \\ \dfrac{\mathrm{d}R}{\mathrm{d}t} = \varepsilon S + \alpha E + \lambda I, \end{cases} \tag{5}$$

where A is the growth rate or new comer; ε is the probability of a susceptible person being directly transformed into an immune person by means of, e.g., isolation; μ is the rate of a susceptible being exposed; β is the rate of an exposed person becoming infectious; and λ is the rate of an infectious person entering into an immune state. The Figure 3B below gives a visual presentation of (5). Note that there is no direction transition between S and I in (5) as illustrated by Figure 2B.

Step 2 Each individual in the network at time t is identified by its state and position in that state group.

Step 3 We will establish an adjacency matrix to describe the influence effects between individuals.

Step 4 Computing the probabilities of transitions between states involves considering the following two aspects (the K-adjacency method).

Step 4.1 The distances between uninfected individuals and their neighborhoods of infected individuals within;

Step 4.2 The number of individuals infected.

Step 5 The full specification of the model is given by combining steps 1 to 4 together with an individual-level representation of (5) that is illustrated in Figure 3B below.

These five steps will help us to run the simulations for the observation of the so-called "Supersaturation Phenomenon" under the probability perspective of all individuals by applying iSEIR mode which help us to identify the "Turning Phase", which are critical for any emergency plan being successful by responding to the challenge any outbreak of pandemics under the emergency in the practice. Thus the iSEIR will be used as a tool for us to discuss how we can establish the framework for the prediction of the critical "Turning Phase" for the emergency implementation response in an epidemic infectious disease outbreak described in next section.

3 The Framework of critical "Turning Phase" for the Implementation of Emergency Response

In this section, we discuss the framework for predicting the "**Turning Term**" using our **iSEIR Model** introduced in [1] which was used to successfully predict the Turning Phase for the COVID-19 epidemic from January 2020 to early of March 2020 in China using only data from Feb.10/2020. As previously discussed, in the battle for epidemic prevention and control of infectious disease outbreak, it is crucial to implement effective prevention measures in the early stages of an outbreak. Furthermore, identifying the beginning and ending points of the

time interval which forms the "Turning Time Period (Time Period)" lets us know how long to expect to implement emergency protocols to effectively flatten the curve. It is possible to make this predictive analysis of the "Turning Time Period" using the iSEIR model through the "**Supersaturation Phenomenon**" elaborated below (see [1]).

3.1 The Concept of "Turning Time Period" for Emergency Risk Management

As discussed in the beginning, not much attention has been paid for the study of critical "**Turning Period**" for the spread of pandemic diseases, and the past experience in the history also tell us that in general it is impossible to conduct reliable prediction of the so-called exactly turning point (time) for any infectious disease spread by human beings due to various dynamics and associated uncertainty which are always out of our control for the emergency risk management plan timely, Thus the key goal of this paper is to establish the framework for the prediction of the "**Turning Period**" (instead of "**Turning Point**") by borrowing key risk indicators called "**Delta**" and "**Gamma**" accepted and used by financial risk management (see [37]) in financial industry in the practice. In this way, it is possible for us to implement reliable predication under the supporting of the new concept "Turning Time Period (Turning Period)" in supporting the planning for emergency risk management by identifying upper and lower limits damage testing, or the loss with a given confidence level as a standard or criteria, and the associated indicators then allow us to identify the different phases and stages of an infectious disease spreading through the iSEIR model, which we elaborate in **Part A** and **Part B** below. Through this approach, it is possible to calculate the critical time period of the "**Turning Time Phase (Turning Phase)**" for the preparation of emergency risk management planning in the practice.

Part A: To Identify Different Time Phases of Epidemics

We propose the identification of three general three phases (time periods) for the emergency response of Epidemic Infectious Diseases Spread paired with medical response actions as elaborated below with the illustration by Figure 3A below.

1) The First Phase. The initial starting stage corresponds to the initial occurrence and prepare for possible emergence plan of a new infectious disease which may or may not transform into a new epidemic.

2) The Second Phase. For our consideration, this is the most important phase which is the so-called "**First Half-Time Phase**" otherwise known as the "Turning Phase" (or "Turning Period") which starts with the beginning of a possible outbreak and includes the delayed epidemic peak by implementation of emergency planning to control the disease spread. The First Half Time phase involves Delta and Gamma indicators (elaborated more in Part B below) to measure the daily change in number of new patients (i.e., the indicator "Delta"), and the rate of the daily change in number of new patients (i.e., the indicator "Gamma"). As shown by Figure 3A below (see also Figure 1 above), the time interval from T_0 to T_1 is our "Turning Phase (Turning Period)", and also makes the end of the "First Half Time Phase" to reach the control for epidemic infectious diseases' spreading.

3) The Third Phase. During this stage, the (epidemic) infectious disease spreading enters the do-called "**Second Half-Time Phase**", which means the peak for the epidemic is gone and the rate of spreading is under a better control position. This is measured in a continuously

decreasing rate of new infections per day, and ultimately leads to any but not exclusively of the following scenarios:

a) the disease completely disappears;

b) an effective vaccine/treatment is introduced;

c) the strain could also disappear and reappear cyclically in seasons, or other reasons.

Of the three phases listed above, the most important time period to identify is the beginning and the ending time points of the "First-Half Phase" (known as the "Turning Period"). This phase is crucial to controlling the outbreak and spread of an epidemic infectious disease after the first case of occurrence.

Thus, being able to identify the "First Half-Phase" is crucial for the reliable prediction of the "Turning Period" (or "Turning Phase") as the ending time point of the Turning Period will allow us to predict when the outbreak of the infectious disease is under the control by the level we may settle (incorporating with ability and capability in the practice).

The next challenge to address is how to identify or predict this Turning Period.

To determine the Turning Period, we look to the occurrence of the so-called "Supersaturation Phenomenon" (elaborated below) based on our iSEIR model (see [1], [38] and also the report by [35]) by running the simulation for the four control variables $S(t), E(t), I(t)$ and $R(t)$ in the iSEIR model (see [1]). These variables are functions of time "t" under the probability framework of individuals involved in the epidemic disease's spread. Our prediction can be achieved once we observe the so-called "**supersaturation phenomenon**", "**the moment where the future value range of T_1 observes both $E(t)$ and $I(t)$ decrease**" as shown by Figure 3B. We determine this by simulating an iSEIR model that incorporates data from the initial daily disease spread (further explained by Part B below) (see also Figure 3B for both $E(t)$ and $I(t)$ at the time t in the future going down).

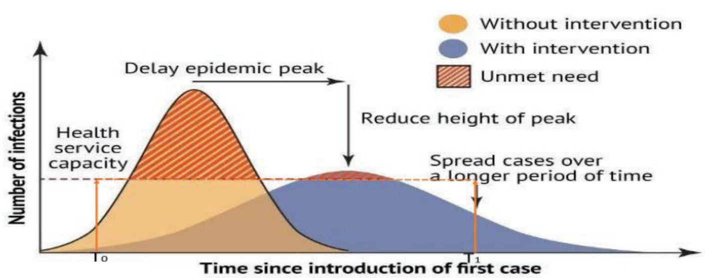

Figure 3A The performance of delay epidemic peak by applying the turning phase structure

Part B: The Prediction of the Turning Period by iSEIR Model with Delta and Gamma Indicators

When COVID-19 first emerged, we suggested using Delta and Gamma indicators to measure the daily change of new patients and the change rate of the daily change for new patients. These variables allowed us to identify the beginning point of the time interval for the Turning Period within China. For example, to identify the starting point T_0 of the Turning Period, the level we considered for Delta was settled as "**no greater than** 10% **daily**"; and Gamma as "**no larger than** 1% **daily**" as the criteria to establish the framework for the "**Dynamic Zero-COVID-19 Policy**" in the practice (see more discussion in the Section 5 below before the end

of this paper).

Next, to predict the future ending time point T_1 of the Turning Period, which measures when the epidemic disease spread is under control, we run numerical simulations based on the iSEIR model as shown in Figure 3B. Note that T_1 is determined to be the time point from which on both variables $E(t)$ and $I(t)$ start to drop (see the illustration given by both Figure 3B and Figure 3A).

The combination of Part A and Part B allowed us to reliably predict the Turning Period of COVID-19 since its first case in Wuhan (China) in late December 2019. Using only the available data released by the Domestic Health Commission of China from Feb.10/2020, we correctly assessed that "**COVID-19 peak around middle to late February, and entering in the Second Half Period around Feb.20/2020**" (see the report given by [38], and also confirmed by WHO's report[35]).

To further understand our predictive simulation, we briefly describe the new idea of our iSEIR model and the related "**Supersaturation Phenomenon**" in the next section.

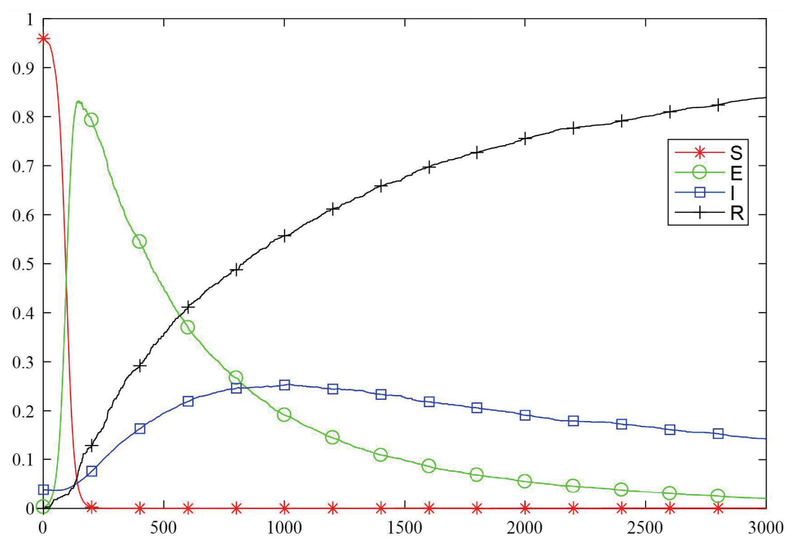

Figure 3B The example of iSEIR modelling simulation: Where the vertical Y-axis represents a standardized unit (normalized unit), the horizontal X-axis represents the time, each one unit is for 10 minutes

3.2 iSEIR Model as a Tool for "Supersaturation Phenomenon"

It is well known that almost all key models such as SEIR and related mathematical tools that exist to model the mechanics of epidemic disease spread are established under deterministic frameworks which assume that all individual behaviors and patterns are uniform (i.e., all behaviors of individuals are homogeneous), but this is not true as each individual's behavior of infecting or being infected is different. In order to have a better way of describing the dynamics of "**Spreading behavior**" in multiplex network at an individual level, to community and then to population levels, we introduced the so-called "**iSEIR model (individual Susceptible-Exposed-Infective-Removed)**" which operates under a probability perspective for each individual (see the reference [1]) around two years ago as an extension of the classic

SEIR one. This "**iSEIR**" model allows us to conduct simulations from the individual level located on the nodes of different community networks by incorporating its uncertainty with the probability to conduct random scenarios study with consideration of the corresponding multiplex networks. The behavior distribution of S, E, I and R can also be numerically simulated from the iSEIR model with properly specified values of parameters on population scales (in the change of percentage), population density, and transfer rate and so to have the simulation results given by Figure 3B above.

Actually the example of simulation results given by Figure 3B based on the iSEIR model suggests that the intensity and extensiveness of the spread of the disease can be lowered by external intervention under a so-called "supersaturation phenomenon" (please see Theorem 3.3 below) for its discussion in mathematics with details. This phenomenon occurs when at some point in the future (denoted by T_1) when both of the variables "$E(t)$" and "$I(t)$" drop in value and do not increase anymore as shown around the x-axis value at the time t is around 1500 units in Figure 3B. Indeed, at the time when $t = 1500$, both variables "$E(t)$" and "$I(t)$" reach to the state so-called the "supersaturation phenomenon". Thus, the "supersaturation phenomenon" in the iSEIR model allows us to predict the turning period for the outbreak of epidemic diseases spread in the application. Indeed, as discussed by Yuan, et al.[1], the first three equations in the system (5) do not contain the variable $R(t)$, we can conclude that the dynamics in (5) can be completely represented at the population-level by the first three equations below (6):

$$\begin{cases} \dfrac{\mathrm{d}S}{\mathrm{d}t} = A - \mu p S(t) - \varepsilon S(t), \\ \dfrac{\mathrm{d}E}{\mathrm{d}t} = \mu p S(t) E(t) - \beta q E(t) I(t) - \alpha E(t), \\ \dfrac{\mathrm{d}I}{\mathrm{d}t} = \beta q E(t) I(t) - \lambda I(t). \end{cases} \tag{6}$$

Now based on the propagation dynamics theory, we know that the behavior of the whole infectious disease spreading system depends on certain propagation threshold parameter R_0, which is called the basic regeneration number. In particular, R_0 has impact on the equilibrium distribution of disease spreading states. Specifically, 1): When $R_0 \leq 1$, the virus spread will eventually disappear; and 2): When $R_0 > 1$, the disease spreading will achieve to an equilibrium distribution. These properties will be confirmed by Theorem 3.3 below in this section.

Denoted by $x := (E, I, S)^{\mathrm{T}}$, then the model system (6) can be expressed as $\frac{\mathrm{d}x}{\mathrm{d}t} := F(x) - V(x)$, where

$$F(x) = \begin{pmatrix} \mu p S E \\ 0 \\ 0 \end{pmatrix}, \tag{7}$$

$$V(x) = \begin{pmatrix} \beta q E I + \alpha E \\ -\beta q E I + \lambda I \\ -A + \mu p S E + \varepsilon S \end{pmatrix}. \tag{8}$$

By defining $G := FV^{-1}$, the available spectral radius (i.e., the basic regeneration number

R_0) can be found from van den Driessche and Watmough[39] to be:

$$R_0 := \rho(A) = \frac{(\beta q)(\mu p)}{(\beta q + \alpha)\lambda}. \tag{9}$$

A plausible initial setting is needed for studying the dynamics of disease spreading. For this we assume there is only one spreader at the beginning, and the initial setting for disease spreading is given by $S(0) = \frac{N-1}{N}, E(0) = \frac{1}{2N}, I(0) = \frac{1}{2N}, R(0) = 0$. Next we provide two lemmas which are taken from Zhao, et al.[40].

Lemma 3.1 *For $\nu > 1$, equation $R = 1 - \mathrm{e}^{-\nu R}$ has two solutions: $R = 0$ and a nontrivial one $0 < R < 1$.*

Proof It is Theorem 1 of Zhao, et al.[40], which completes the proof.

Lemma 3.2 *For equation equation $R = 1 - \mathrm{e}^{-\varepsilon R}$, where $\varepsilon = \frac{\lambda+\alpha}{\alpha}$, we have that for a fixed α, R increases as λ increases. Similarly, given a fixed λ, R decreases as α increases.*

Proof It is Theorem 2 of Zhao, et al.[40], which completes the proof.

In the following we aim to establish a general theoretic result for final removal proportion, to be presented in Theorem 3.3, for virus spreading that follows the iSEIR model. Here the final removal proportion in virus spreading dynamics is defind as $R := \text{final}\{R(t)\} = \lim\limits_{t\to\infty} R(t) = R(\infty)$, which can be used to measure the level of virus influence in the practice.

When the dynamics of Infectious Diseases spreading following the iSEIR model eventually achieves equalibrium, it is reasonable to assume that $A \approx 0$, ε is close to 0, $I \approx E$ (i.e., the proportion of the infected being lurkers is nearly zero), and the network size N is suffciently large. With these assumptions, we have the following key result.

Theorem 3.3 *Let $\nu = \frac{\mu p}{\alpha+\lambda}$. Then when $\mu p > \alpha + \lambda$, the equation $R = 1 - \mathrm{e}^{-\nu R}$ has two solution: Zero and a nontrivial solution R, where $0 < R < 1$.*

Proof Based on the system of Equations (5) and (6), we have

$$\frac{\mathrm{d}R}{\mathrm{d}S} = \frac{\varepsilon S + \alpha E + \lambda I}{A - \mu p S E - \varepsilon S}. \tag{10}$$

By using the assumption that $A \approx 0$, and the Equation (10) we have

$$\mathrm{d}R = \frac{\varepsilon S + \alpha E + \lambda I}{-\mu p S E - \varepsilon S} \mathrm{d}S. \tag{11}$$

Now integrating both sides of Equation (11) from the initial time to the stationary time and nothing that ε is close to 0, it follows that

$$\int_0^{\infty} \mathrm{d}R = \int_0^{\infty} \frac{\alpha E + \lambda I}{-\mu p S E} \mathrm{d}S, \tag{12}$$

then we have that

$$R(\infty) - R(0) = \frac{\alpha E + \lambda I}{-\mu p S E} [\ln(S(\infty)) - \ln(S(0))]. \tag{13}$$

Noting that $S(0) = \frac{N-1}{N} \approx 1 (N \to \infty)$, $R(0) = 0$, $S(\infty) = 1 - R(\infty) = 1 - R$, and $R(\infty) = R$, it follows that

$$R = -\frac{\alpha E + \lambda I}{\mu p S E} \ln(1 - R), \tag{14}$$

which means that

$$-\frac{\mu p S R}{\alpha+\lambda(I/E)}=\ln(1-R). \tag{15}$$

By Equation (15) it follows that

$$\mathrm{e}^{-\frac{\mu p S R}{\alpha+\lambda(I/E)}}=1-R, \tag{16}$$

and thus we obtain the following transcendental equation:

$$R=1-\mathrm{e}^{-\frac{\mu p}{\alpha+\lambda(I/E)}R}, \tag{17}$$

and by the assumption that $I\approx E$, it follows that

$$R=1-\mathrm{e}^{-\frac{\mu p}{\alpha+\lambda}R}. \tag{18}$$

Now by applying Lemma 3.1 above, let $\nu:=\frac{\mu p}{\alpha+\lambda}$, we have $\nu>1$, this implies that the conclusion is true, which completes the proof.

Remark 3.4 Theorem 3.3 gives an equation that must be satisfied by the steady-state removal proportion R for the dynamics of the Infectious Diseases spreading follow the iSEIR model. This result provide guidance to conduct numerical simulations for the prediction of "**Turning Period**" (for the preparation of the emergency risk management in the practice in dealing with the event of COVID-19 epidemic), which will be discussed in Section 4 below, where the supersaturation phenomenon can be observed in the dynamics of Infectious Diseases spreading if "lurkers do not exist" in the network of community for the population such as the case under the implementation of the "**Lockdown and Isolation Control Program**" in Wuhan, China since Jan.23/2020 to the early March, 2022 in dealing with the COVID-19 epidemic (see the reference [35]).

4 The Prediction of "Peak Period" for COVID-19 in Wuhan from Late Jan./2020 to Early Feb./2020

The methodology outlined above is what we expect when modeling epidemic disease, including COVID-19 which has become a global pandemic since the epidemic in Wuhan in late December 2019. Taking into account the performance of intervention controls (i.e., Quarantine program in Wuhan, Hubei province (see [36])) implemented since Jan.23/2020 at a domestic level by the Chinese government, we predicted the "Peak Time Period" of COVID-19 in China using our iSEIR model (see [32, 33]), [38], and [41] in two separate reports on Feb.6/2020 and Feb.10/2020 (see also [34–36]).

By following the discussion above, first of the first, we truly believe that "**Turning Period**" (or say, "**Turning Phase**") for **COVID-19** is not a single time point, but a period of time interval associated with at least the two indicators called "Delta" and "Gamma" which are key two measurements used in the practice of risk management in financial industry.

4.1 Using Delta and Gamma to identify the Starting Date of "Turning Period" of COVID-19 in China was Feb.1/2020

Based on the concepts of "Delta" and "Gamma" which are Greek letters used in financial risk management: "Delta" to describe the daily change of both "E" and "I"; and "Gamma"

accounts for the speed of daily change for the number of new confirmed patients for both "E" and "I", we plan to predict the "**Turning Phase**" for COVID-19 in China, but we need first to identify the "**Starting Point**" of COVID-19's Turning Period. Indeed by using the daily information from Jan.23, 2020 to Feb.6, 2020, we first observed that "Delta" and "Gamma" were below around 20% and around 2% daily, respectively, "**for 5 consecutive days since Feb.1/2020**", which led us to conclude that "**Feb.1/2020**" heralds the start towards the situation peaking by combining the explanation under the supporting by the simulations results based on the iSEIR model given by Figure 4 below (see also Figures 5, 6 and 7 below), and thus we first have the following conclusion (see also the report in [32] with more in details).

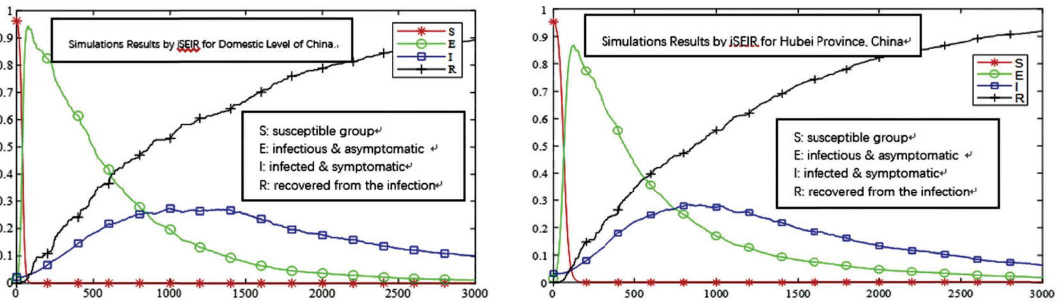

Figure 4 The simulations results by iSEIR model on data of Feb.10, 2020 for Domestic level of China, and Hubei Province, China; where the vertical Y-axis represents a standardized unit (normalized unit), the horizontal X-axis represents the time, each one unit if for 10 minutes.

The Conclusion A: we have

The date of Feb.1/2020 was the beginning time of the COVID-19 epidemic in China (including Wuhan, Hubei); namely, the starting date for the "**Turning Period**" of China's COVID-19 epidemic (see also the report given by [32] released on Feb.7/2020). This is also verified by the official daily data released by NHC of China on February 28/2020 (see the reports given by [34], [35], [38] and [41]).

Indeed, from Table 1 below, we see that Delta and Gamma are within or below around 20% and around 2% respectively for 5 consecutive days since Feb.1/2020. This also confirms the conclusion that Feb.1/2020 is the starting date for the Turning Period of the COVID-19 epidemic.

4.2 The Prediction of Second Half-Time Phase after "Turning Period" for COVID-19 in China: From the Middle Feb./2020 to Late Feb./2020"

Using the concept of Turning Phase and the application of the iSEIR model on Feb.10/2020, based on 3 weeks of available daily data (from Jan.23/2020 to Feb.10/2020) released by NHC of China, our simulation successfully modeled the future pattern of official data released almost 3 weeks later with the explanation of results by Figure 4 (see also Figures 5, 6 and 7 below), as shown by the Conclusion B below (see also the reports from [32] and [33], see also the inputs data and parameters for iSEIR model given by Tables 5∼7 with incorporation of official data provided by NHC as of Feb.10/2020).

Table 1 The daily change of infected COVID-19 patients by the National Health Protection Committee of China from Feb.1 to Feb.6/2020

Times	Feb.01/ 2020 Turning point	Feb.02/ 2020	Feb.03/ 2020	Feb.04/ 2020	Feb.05/ 2020	Feb.06/ 2020
COVID-19 Infected Patients in Hubei	9,074	11,177	13,522	16,678	19,665	22,112
COVID-19 Infected Patients in rest of China	5,306	6,028	6,916	7,646	8,353	9,049
COVID-19 Infected Patients in China	14,380	17,205	20,438	24,324	28,018	31,161
Delta: Daily Change of COVID-19 Infected Patients in Hubei	27%	23%	21%	23%	18%	12%
Delta: Daily Change of COVID-19 Infected Patients in rest of China	14%	14%	15%	11%	9%	8%
Delta: Daily Change of COVID-19 Infected Patients in China	22%	20%	19%	19%	15%	11%
Gamma: Speed of Daily Change of COVID-19 Infected Patients in Hubei	16%	−14%	−9%	11%	−23%	−31%
Gamma: Speed of Daily Change of COVID-19 Infected Patients in rest of China	−26%	−3%	8%	−28%	−12%	−10%
Gamma: Speed of Daily Change of COVID-19 Infected Patients in China	1%	−11%	−4%	1%	−20%	−26%

The Conclusion B We have:

First, The dare of Feb.1/2020 was the initial starting point for the turning point of the **COVID-19** epidemic situation in China, combined with the simulation analysis of our internal model iSEIR in considering the current situation and the "**isolation control program**" currently implemented in China, the time interval for controlling the COVID-19 outbreak should be in the period from "**Middle of Feb./2020 to before the end of Feb./2020**" (see also the reports given by [32] and [33]) (and numerical results by Figure 4 and Tables 2∼3), and we have the following findings:

1) The number of infectious and asymptomatic ("E") (in % change) (for China and Hubei) will reach a peak in about 2 days (Feb.12/2020), and then after about 7 days (Feb.17/2020), the rate of increase will decrease to less than 10%;

2) The daily increase in the number of people infected and symptomatic ("I") (for China and Hubei) is a steady downward trend, and the rate will decrease to within 10% after about 14 days (Feb.24/2020); and

3) The proportion of people recovering from infection ("R") (for China and Hubei) will return to more than 80% after about 17 days (Feb.27/2020).

Second, we earmarked the second half of Feb./2020 (around Feb.20/2020) as the time period when the peak would happen as shown by our simulation results shown below on Feb.10/2020 (later confirmed by the data released by NHC of China). Our conclusion that

"the number of infectious and asymptomatic (E) (in % change) will reach a peak in about 2 days (Feb.12/2020)" was confirmed by the report of NHC:

Table 2 The daily data of COVID-19 in China

Item	2020/2/19	2020/2/18	2020/2/17	2020/2/16	2020/2/15	2020/2/14	2020/2/13
The number 1 (I)	126,363	135,881	141,552	150,539	158,764	169,039	177,984
Its Delta	−7.0%	−4.0%	−6.0%	−5.2%	−6.1%	−5.0%	−1.9%
Its Gamma	74.8%	−32.9%	15.2%	−14.8%	20.9%	168.0%	−4.9%
The number 2 (E)	589,163	574,418	560,901	546,016	529,418	513,183	493,067
Its Delta	2.6%	2.4%	2.7%	3.1%	3.2%	4.1%	4.6%
Its Gamma	6.5%	−11.6%	−13.0%	−0.9%	−22.5%	−10.7%	2.7%
Item	2020/2/12	2020/2/11	2020/2/10	2020/2/9	2020/2/8	2020/2/7	
The number 1 (I)	181,386	185,037	187,728	187,518	188,183	189,660	
Its Delta	−2.0%	−1.4%	0.1%	−0.4%	−0.8%	1.9%	
Its Gamma	37.6%	−1380.0%	−131.7%	−54.6%	−140.1%	−1271.8%	
The number 2 (E)	471,531	451,462	428,438	399,487	371,905	345,498	
Its Delta	4.4%	5.4%	7.2%	7.4%	7.6%	10.0%	
Its Gamma	−17.3%	−25.8%	−2.3%	−3.0%	−23.7%	−9.2%	

Notes: The Number 1 refers to the number of Close contracts under the monitor in hospital (i.e., "I"); The Number 2 refers to the number of Close contracts (i.e., "E").

"The above results are found to conform very well to the actually observed data from the National Heath Commission (NHC) of China. Specifically, the daily official data show that Feb.11/2020 is the peak time with its Delta value achieving 5.4% daily, the highest one from February 1, 2020 through to February 25, 2020. This corroborates our prediction that around February 12, 2020 achieves the outbreak peak based on our iSEIR model."

The true daily official data of NHC indeed shows that Feb.11/2020 was the peak time with its Delta value (the daily change for the number of close contacts people (with patients)) at 5.4% daily, the highest value in the date range from Feb.1 through to Feb.25/2020. This corroborates our prediction of around Feb.12/2020 as the peak time based on our iSEIR model.

4.3 The Concept of "Turning Period" Works in Supporting the Prediction for COVID-19 Epidemic in Early Yr2000

Based on the study and discussed above, it seems that the iSEIR model is able to predict the peak time period for the Infectious Diseases spreading of COVID-19 epidemic with an approximate interval encompassing a larger time period. Based on our working in this issue, we strongly believe that the traditional concept "**Turning Point**" is not an accurate term to use for the predication of dynamic mechanics for Infectious Diseases spreading, but the new concept "**Turning Period**" should work for us to describe the behaviors of mechanics for Infectious Diseases spreading in the practice.

The true data also shows that our prediction for "The second half-time phase after the **Turning Period** in Feb./2020" is also confirmed (backed) by the World Health Organization

(WHO), whose own data shows that the Chinese cases of COVID-19 levelled off sometime during the week of Feb.14/2020, as WHO director-general Tedros Adhanom Ghebreyesus stated that in a press conference on Feb.24/2020 that the epidemic in China "has been declining steadily" in average since Feb.2/2020 (see reports given by [34–36]).

By following the so-called "follow-up analysis" in determining the accuracy of our iSEIR model using official data from Feb.11/2020 to Feb.21/2020, we have the following major findings (see also reports by [34] and [41]):

1) Since Feb.17/2020, the "Delta" for the number of close contacts has declined rapidly to 2.4% of Feb 23/2020, and 2.9% of Feb.22/2020 (but one jumping being 5.4% of as of Feb.20/2020) (Table 3 below);

2) Since Feb.17/2020, the death rate has remained around in the level of 3% (Table 4 below); and

3) Since Feb.17/2020, the "Delta" of the number of infected people has also declined to around the range from 2% to 4% (Table 5 below).

In addition, as Feb.17/2020 and Feb.18/2020 had the highest number of confirmed cases in China (Table 5), and Hubei, respectively, it confirms that "we have reason to believe that the inflection point has emerged on Feb.17/2020 and Feb.18/2020, thus this fact validated the prediction we made on Feb.7/2020" (see more from the reports given by [32], [33], [38] and [41]).

Table 3 People with close contact with patients

Date	Domestic	Daily Change	Hubei	Daily Change in Hubei
2020/2/12	471,531	4.3%	158,377	3.9%
2020/2/13	493,067	4.4%	166,818	5.1%
2020/2/14	513,183	3.9%	176,148	5.3%
2020/2/15	529,418	3.1%	183,183	3.8%
2020/2/16	546,016	3.0%	191,434	4.3%
2020/2/17	560,901	2.7%	199,322	4.0%
2020/2/18	574,418	2.4%	206,087	3.4%
2020/2/19	589,163	2.6%	214,093	3.9%
2020/2/20	606,037	2.9%	225,696	5.4%
2020/2/21	618,915	2.1%	234,217	3.8%
2020/2/22	628,517	1.6%	240,937	2.9%
2020/2/23	635,531	1.1%	246,781	2.4%
2020/2/24	641,742	1.0%	251,265	1.8%
2020/2/25	647,406	0.9%	255,750	1.8%
2020/2/26	652,174	0.7%	259,491	1.5%
2020/2/27	656,054	0.6%	262,195	1.0%
2020/2/28	658,587	0.4%	263,916	0.7%
2020/2/29	660,716	0.3%	265,617	0.6%

Table 4 Case fatality rate (cumulative)

Date	Domestic # of death	Daily change	Death # in Hubei	Daily Change in Hubei
2020/2/12	1,259	2.29%	1,202	2.55%
2020/2/13	1,380	2.16%	1,318	2.54%
2020/2/14	1,523	2.29%	1,457	2.68%
2020/2/15	1,665	2.43%	1,596	2.84%
2020/2/16	1,770	2.51%	1,696	2.91%
2020/2/17	1,868	2.58%	1,789	2.98%
2020/2/18	2,004	2.70%	1,921	3.11%
2020/2/19	2,118	2.84%	2,029	3.25%
2020/2/20	2,236	2.96%	2,144	3.40%
2020/2/21	2,345	3.07%	2,250	3.55%
2020/2/22	2,442	3.17%	2,346	3.66%
2020/2/23	2,592	3.36%	2,495	3.88%
2020/2/24	2,663	3.43%	2,563	3.96%
2020/2/25	2,715	3.48%	2,615	4.01%
2020/2/26	2,744	3.50%	2,641	4.03%
2020/2/27	2,788	3.54%	2,682	4.07%
2020/2/28	2,835	3.58%	2,727	4.11%
2020/2/29	2,870	3.60%	2,761	4.13%

Table 5 Confirmed patients (cumulative value)

Date	Domestic	Daily Change	Hubei	Daily Change in Hubei
2020/2/12	58,761	31.6%	47,163	41.4%
2020/2/13	63,851	8.7%	51,986	10.2%
2020/2/14	66,492	4.1%	54,406	4.7%
2020/2/15	68,500	3.0%	56,249	3.4%
2020/2/16	70,548	3.0%	58,182	3.4%
2020/2/17	72,436	2.7%	59,989	3.1%
2020/2/18	74,182	2.4%	61,682	2.8%
2020/2/19	74,576	0.5%	62,031	0.6%
2020/2/20	75,891	1.8%	63,088	1.7%
2020/2/21	76,288	0.5%	63,454	0.6%
2020/2/22	76,936	0.8%	64,084	1.0%
2020/2/23	77,150	0.3%	64,287	0.3%
2020/2/24	77,658	0.7%	64,786	0.8%
2020/2/25	78,064	0.5%	65,187	0.6%
2020/2/26	78,497	0.6%	65,596	0.6%

Table 5 (continued) Confirmed patients (cumulative value)

Date	Domestic	Daily Change	Hubei	Daily Change in Hubei
2020/2/27	78,824	0.4%	65,914	0.5%
2020/2/28	79,251	0.5%	66,337	0.6%
2020/2/29	79,824	0.7%	66,907	0.9%

Table 6 The Change of existing confirmed infected patients

Date	Domestic	Daily Change	Hubei	Daily Change in Hubei
2020/2/11	38,800		29,659	
2020/2/12	51,860	33.7%	42,789	44.3%
2020/2/13	55,748	7.5%	46,806	9.4%
2020/2/14	56,872	2.0%	48,175	2.9%
2020/2/15	57,416	1.0%	49,030	1.8%
2020/2/16	57,927	0.9%	49,847	1.7%
2020/2/17	**58,016**	**0.2%**	50,338	**1.0%**
2020/2/18	57,802	**−0.4%**	**50,633**	**0.6%**
2020/2/19	56,727	−1.9%	50,091	−1.1%
2020/2/20	55,389	−2.4%	49,156	−1.9%
2020/2/21	53,285	−3.8%	47,647	−3.1%
2020/2/22	51,606	−6.8%	46,439	−5.5%
2020/2/23	49,824	−6.5%	45,054	−5.4%
2020/2/24	47,672	−7.6%	43,369	−6.6%
2020/2/25	45,604	−8.5%	41,660	−7.5%
2020/2/26	43,258	−9.3%	39,755	−8.3%
2020/2/27	39,919	−12.5%	36,829	−11.6%
2020/2/28	37,414	−13.5%	34,715	−12.7%
2020/2/29	**35,329**	**−11.5%**	**32,959**	**−10.5%**

4.4 The Overview of Prediction Based on the iSEIR Model

Here we review the results based on our iSEIR model from Feb.10, 2020 by presenting the original report's results in two parts as follows.

4.4.1 The Outlook Report for COVID-19 as Feb.10/2020 (see [33] and [38])

Based on our iSEIR model and the data from China's novel COVID-19 epidemic released as of Feb.10/2020 (see also reports by [33] and [38]), we reach the following three conclusions I, II and III (see also corresponding inputs for the simulations by applying iSEIR model are given by Tables 5∼6 and incorporation with official data released by NHC of China on Feb.10, 2020).

I) COVID-19 on the Domestic Level of China. We have that:

1) On the domestic level, the change in number of close contacts (E) reached a peak in about 2 days (around Feb.12/2020), and then after about 7 days (i.e., around Feb.17, 2020),

the number of close contacts began a stable in the average downward trend of less than 3% (see also Table 3);

2) On the domestic level, the daily decrease in the number of people infected (I) is also a steady downward trend as of date, and is within around about 10% after approximately 14 days (Feb.24/2020); and

3) On the domestic level, the proportion of people recovering from infection (R) will quickly return to around 90% after about 17 days (around Feb.27/2020).

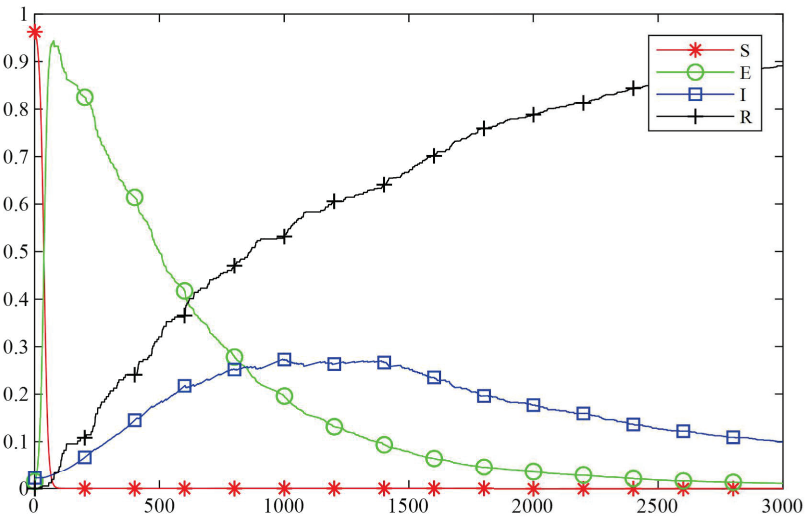

Figure 5 The simulations results by iSEIR model on data of Feb.10, 2020 for domestic level of China: Where the vertical Y-axis represents a standardized unit (normalized unit), the horizontal X-axis represents the time, each one unit is for 10 minutes

II) COVID-19 on the Level of Hubei Province. By using 144,279 close contacts, 31,728 confirmed infections and 3.07% mortality as the core input parameters, as of Feb.10, 2020, our simulation analysis results show (the same above, the vertical Y-axis represents one unit of standardization (from 0 to 1) and the horizontal X-axis represents Time whereby one unit is "10 minutes", that is, one day is "144 units"):

1) In Hubei Province, the number of close contacts (E) peaks after about 2 days (around Feb.12/2020), and then steadily declines with a change of less than 4% after about 6 days (around Feb.16, 2020);

2) In Hubei Province, the daily decrease of the number of people infected (I) also shows a steady downward trend, reaching a peak in about 7 days (Feb.17/2020), and then decreasing at a rate of around about 7%; and

3) In Hubei Province, the proportion of people who recovered from infection (R) quickly recovers to around 90% after about 17 days (around Feb.27/2020).

III) COVID-19 on the Level of Wuhan City. Using 83,917 close contacts (estimated), 18,454 confirmed infections, and 4.05% mortality rate as the key input parameters as of Feb. 10, 2020, combined with the current intervention situation in Wuhan, our simulation analysis results show (the same above, the vertical Y-axis represents one unit of standardization (from

0 to 1) and the horizontal X-axis represents time whereby one unit is "10 minutes", that is, one day is "144 units"):

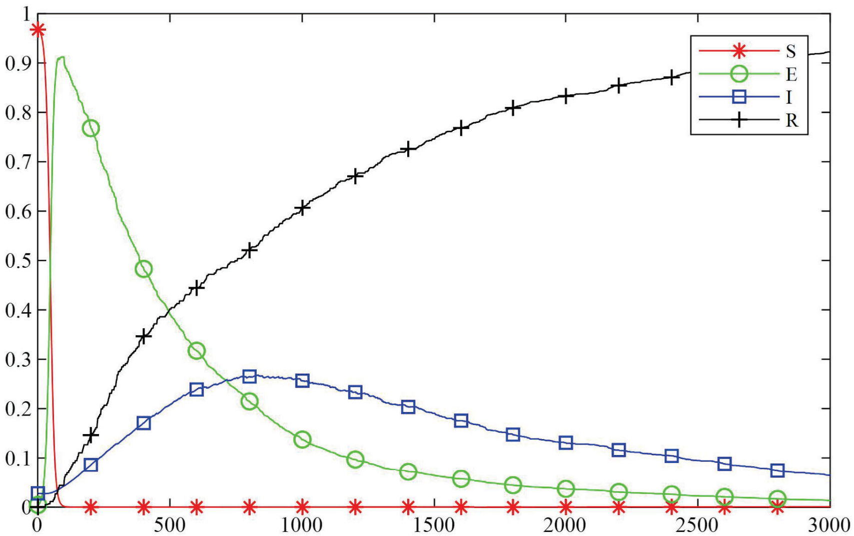

Figure 6 The simulations results by iSEIR model on data of Feb.10, 2020 for Hubei province, China: where the vertical Y-axis represents a standardized unit (normalized unit), the horizontal X-axis represents the time, each one unit is for 10 minutes

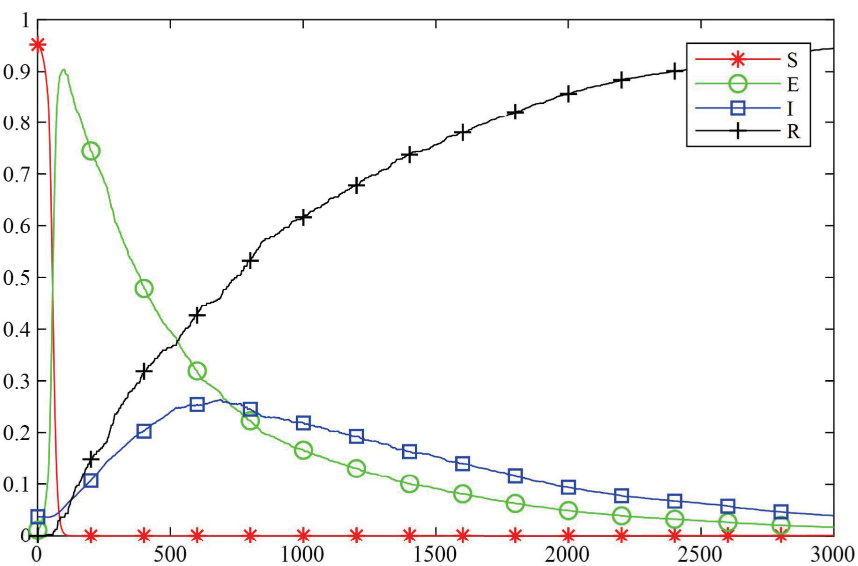

Figure 7 The simulations results by iSEIR model on data of Feb.10, 2020 for city of Wuhan, China: where the vertical Y-axis represents a standardized unit (normalized unit), the horizontal X-axis represents the time, each one unit is for 10 minutes

1) In the city of Wuhan, after about 4 days, the daily variation of the number of close contacts (E) is a stable downward range of about 4%;

2) In the city of Wuhan, the daily decrease of the number of people infected (I) is also a steady downward trend, reaching a peak in about 4 days, and then decreasing at a rate of around at 4%; and

3) In the city of Wuhan, the proportion of people (R) recovering from infection quickly recovers to close to 90% after about 17 days (around Feb.27/2020).

4.4.2 Entering into the Second Half of the COVID-19 Epidemic on Feb.20/2020

On Feb.16/2020, the reports we released (see [38] and [41]) states that "Once the peak has been identified, a different approach has to be taken with regard to city management, economic development and epidemic control measures", this is actually in-line with Chinese leader's address on Feb.23/2020, where he stressed that the country needs to resume production and normal life. Since the COVID-19 virus could be spread asymptomatically, being able to model its trend is crucial to timeline projections. Also, Dr. Bruce Aylward, an epidemiologist who led a 25-member team from WHO to conduct a 9-day field study trip to Beijing, Guangdong, Sichuan and Hubei, shared this viewpoint. "They are using big data, artificial intelligence in places", Dr. Aylward said, "It's a technology-powered and science-driven agile response at a phenomenal scale" (see [34], [35], [41], and also the report in [36]).

5 What We Learned from the Prevention of COVID-19 Epidemic in China since Early Year 2020

Our predictions based on the iSEIR model on Feb.6/2020, were validated by the official data released by the NHC on COVID-19. The numbers of China and its six regions (including Hubei Province and Hubei's five cities: Wuhan, Xiaogun, Suizhou, Huanggang, and Huangshi) were as follows: 76,936 confirmed patients in domestic level of China as of Feb. 22 (in which 64,084 confirmed cases from Hubei province) and 12,852 in other provinces, 62,8517 people with close contacts (with patients), and a 3.17% mortality rate of confirmed infected. Our conclusions, originally published on Feb. 16/2020, are as follows (see [34], [35], [38] and [41]) by two parts.

The First: We have that

1) Feb.1/2020, is the starting point for the formation of the epidemic's Turning (Inflection) Point which will form around mid-February (see [32] for the concept and definition of "Turning (Inflection) Point" formation and the establishment of supporting standard indicators); and

2) We reported that the COVID-19 epidemic in China has reached controllable measures in our Feb.16/2020, report, and that we are now entering the second-half of the struggle against COVID-19 in China (see [33], [38], [41]).

The Second: There appears the following similar development trends in Hubei province, as well as in Wuhan, Xiaogan, Suizhou, Huanggang and Huangshi (with reference to the figure below):

1) The number of close contacts (represented by "E") begins to decline rapidly after about Feb.16/2020, then, in a short period of time, the number of close contacts follows a stable downward change of less than 10%; and

2) The daily variation of change of new confirmed infected (represented by "I") is also in a stable downward variation. In a very short time (no more than 3 to 10 days), the number

of daily change for infected people is within the range of 10% (but higher than the overall average).

Using the official data for COVID-19 epidemic released as of Feb.21/2020 by NHC of China, the four tables (Tables 3∼6) show the daily changes in the number of close contacts, the number of infections, and the death rate of confirmed patients in five cities (Wuhan, Xiaogan, Suizhou, Huanggang and Huangshi). The official data confirms the predictive analysis reports we made on Feb.6/2020, and Feb.10/2020, and we have the following findings:

1) Since Feb.17/2020, the daily variation of close contacts in all seven simulated areas has declined rapidly to 4% (the domestic average change is lower than that in Hubei province);

2) Since Feb.17/2020, the death rate of confirmed patients in China has remained within 3%, but the death rate of confirmed patients in Hubei Province is slightly higher than that in China, which is remains at about 3.5%; and

3) Since Feb.17/2020, the daily variation of the number of infected people in all seven simulated areas has also declined to within 4% (the daily variation of Wuhan is slightly higher than that of the whole country, but that of Xiaogan, Suizhou, Huanggang and Huangshi remains within 2%).

a) Based on the number of existing confirmed cases, we determined the inflection time around Feb.17/2020. Based on the number of existing confirmed cases in China and Hubei Province, we used the iSEIR model on Feb.11/2020, to predict that the dates of Feb.17/2020 and Feb.18/2020 would have the highest number of existing confirmed cases in China and Hubei Province, respectively. Today (as of Feb.22/2020 for the dated used in the original reports given by [33], [34], [38] and [41]), the number of existing confirmed cases and the highest confirmed cases in China and Hubei Province have been reduced by more than 5,700 and 5,000 respectively. Considering the three-day screening in Hubei Province from Feb.17/2020 to Feb.19/2020, we have reason to believe that the true Turning (Inflection) Point based on the number existing confirmed cases emerged at approximately Feb.17/2020.

b) Through a comprehensive analysis of Hubei province, we determine the inflection time period around between Feb.17/2020 and Feb.19/2020, the data set combined with the previous conclusion lead us to believe that the COVID-19 infection in China (including Wuhan, Hubei) has been fully controlled since mid-February/2020, with Feb.18/2020 as the most precise date (we arrive at Feb.18/2020 as after Feb.17/2020, the daily change of confirmed patients is less than 1% in negative numbers).

In summary, we believe that the iSEIR model is a reliable predictor for the Turning Period of the struggle against COVID-19 through introducing concepts of "Turning Phase" and "Supersaturation Phenomenon". This model accounts for intervention policies and methods such as isolation control programs (e.g., quarantine); such as those implemented in February/2020 in China (see [34] and [35]). Beyond using our iSEIR model for the COVID-19 in China from late December to early March, 2020, we hope the predication framework established in this paper can be further used to study the outbreaks worldwide.

When we incorporate the public official data released by the Chinese government since Jan.23, 2020, our iSEIR simulation allowed us to conclude that: The date of Feb.1/2020 is the starting point for the formation of the turning point of the COVID-19 epidemic situation in

China. Considering the intervention efforts implemented at the state-level, the time period for the control of the COVID-19 epidemic should be around mid-February 2020, and at least by the end of February/2020 (see the original report released [33], [34] and [38] for more details).

Table 7 The General Initial Inputs for the Simulation of iSEIR Model

Date: February 10, 2020. The data in highlight with red color means on the true real scene for the simulation	
Name of Parameter	Values
# of simulations	100 times of simulations
N: # of groups/communities	Specified in simulation
M: # of cities	10
ρ: distribution density	0.4
c: distance	base on Euclidean distance formula
T: time steps	1–3000 (one unit is around 10 minutes, or 5 minutes)
N: population	The input based on the true real scene for the simulation
i, j, k: random individual	Uniform distribution
i, j, k:	The range is from N specified by true real scene
γ	The input based on the true real scene for the simulation
A	$= 0.000001$
p_{ij}	$= 1$, if the distance of i and $j \leq c$; $= 0$, otherwise.
q_{jk}	$= 1$, if the distance of j and $k \leq c$; $= 0$, otherwise.
μ_i	$= 1$, if in [0.0001, 1]; $= 0$, otherwise.
ϵ_i	$= 1$, if ≤ 0.0001; $= 0$, otherwise.
β_i	$= 1$, if in [0.001, 1]; $= 0$, otherwise.
α_j	$= 1$, if ≤ 0.001; $= 0$, otherwise
λ_k	$= 1$, if $\leq$ the specified value for a given input parameters (γ) $= 0$, otherwise.
Other parameters	Based on the situation to specify

Before arriving at our final remarks, we want to consider the following with regards to the current global state of the COVID-19 epidemic:

1) The virus can be spread by infected and asymptomatic individuals; and

2) At current, there is no fully effective medicine or treatment.

With these conditions, it is important to implement the so-called "dynamic zero-COVID-19

policy" ongoing basis in the practice, this menas that ideally it is best to clean all infectious disease and their epidemics and virous spreading (e.g., for COVID-19 epidemic), but in the reality, it is hard to clean, or keep away from infectious diseases. Thus to design and establish reasonable criteria as the bottom lines for the control of infectious diseases spreading is a critical job! The predication framework and method developed in this paper show that they are able to provide the reliable peak period by using the new concept "Turning Term (Phase) Structure" for the infectious diseases spreading timely and accurate, which would also provide adequate time for the government, hospitals, essential industry sectors and services to meet peak demands and to prepare aftermath planning, and associated quantitative criteria can be used to monitor the daily change ongoing basis. Therefore the predication framework of the "Turning Term Structure" established in this paper in dealing with the emergency plan for the occurring such as COVID-19 epidemic, or any other kinds of unexpected natural disasters is expected to be a useful and powerful tool for us to implement the so-called "dynamic zero-COVID-19 policy", or emergency plan quickly in the practice.

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